Macro Risks and Term Structure of Interest Rates

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Aggregate Demand and Supply Shocks

- Define aggregate demand/supply shocks using minimal theoretical restrictions (Blanchard, 1989):
  - Aggregate demand (AD): moves GDP growth and inflation in the same direction
  - Aggregate supply (AS): moves GDP growth and inflation in opposite directions
- Macro risks=second and higher order moments of AD/AS shocks
- Identification of aggregate demand (AD) and aggregate supply (AS) shocks is important in many areas of economics

Macroeconomics

- Which shocks drive recessions?
- Which shocks drive long-term GDP growth?
- Our contribution:
  - A novel method to extract AD/AS shocks exploiting non-Gaussian properties of data
  - Characterizing US business cycles as AD/AS (e.g., Great Recession)
  - Supply shocks have permanent impact on real GDP, while demand shocks don't

Asset Pricing

- Explaining bond risk and term premia:
  - Most of the literature uses financial factors (e.g., Campbell and Shiller, 1991)
  - Most of the literature which deals with macro factors relies on level factors (e.g., Ludvigson and Ng, 2009): exceptions are Wright (2011) and Bansal and Shaliastovich (2013)
- Economic insight: bond risk and term premia should be higher (lower) in aggregate supply (aggregate demand) environment
- Our contribution:
  - Non-Gaussian AD/AS macro risk factors drive substantial variation in bond risk-premia
  - AD/AS macro risks factors affect bond risk and term premia differently

Macroeconomic Shocks

- Shocks to real GDP growth and inflation:

$$g_{t+1} = E_t[g_{t+1}] + \epsilon^g_{t+1},$$

$$\pi_{t+1} = E_t[\pi_{t+1}] + \epsilon^\pi_{t+1}.$$

- Modeling using demand and supply shocks:

$$\epsilon^g_{t+1} = \underbrace{\sigma^d_g}_{>0} u^d_{t+1} + \underbrace{\sigma^s_g}_{>0} u^s_{t+1},$$

$$\epsilon^\pi_{t+1} = \underbrace{\sigma^d_\pi}_{>0} u^d_{t+1} - \underbrace{\sigma^s_\pi}_{>0} u^s_{t+1},$$

$$Cov(u^d_{t+1}, u^s_{t+1}) = 0, Var(u^d_{t+1}) = Var(u^s_{t+1}) = 1.$$

Macroeconomic Environments

- If supply and demand shocks are heteroskedastic, $Cov_t(\epsilon^g_{t+1}, \epsilon^\pi_{t+1})$ will vary over time:

$$Cov_t(\epsilon^g_{t+1}, \epsilon^\pi_{t+1}) = \sigma^d_g \sigma^d_\pi Var_t(u^d_{t+1}) - \sigma^s_g \sigma^s_\pi Var_t(u^s_{t+1})$$

- Demand shock environment: large $Cov_t(\epsilon^g_{t+1}, \epsilon^\pi_{t+1}) \Rightarrow$ nominal bonds hedge well

- Supply shock environment: small $Cov_t(\epsilon^g_{t+1}, \epsilon^\pi_{t+1}) \Rightarrow$ nominal bonds hedge poorly

Identification

- **Demand and supply shocks are not identified with Gaussian shocks:** 4 coefficients $(\sigma_g^d, \sigma_\pi^d, \sigma_g^s, \sigma_\pi^s)$ to identify but only 3 moments to match (2 variances and covariance)

- Approach: use non-Gaussian data aspects for the identification:
  - Is macroeconomic data non-Gaussian?
  - How to model non-Gaussian features?

Modeling Demand and Supply Shocks

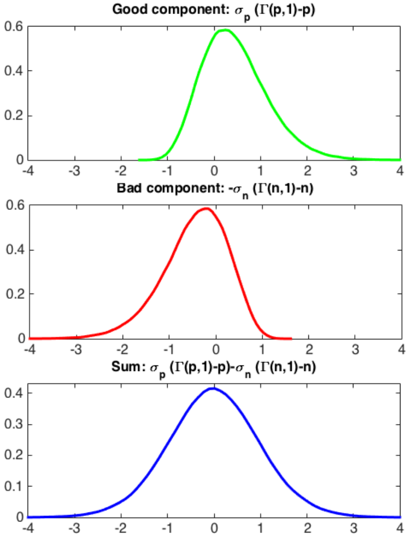
- Demand (and supply) shocks modeled using Bad Environment-Good Environment (BEGE) structure (Bekaert and Engstrom, JPE 2016):

$$u^d_{t+1} = \sigma^d_p \underbrace{\omega^d_{p,t+1}}_{\text{good shock}} - \sigma^d_n \underbrace{\omega^d_{n,t+1}}_{\text{bad shock}}$$

- Shocks follow demeaned gamma distributions:

$$\left.\begin{array}{l} \omega^d_{p,t+1} \sim \Gamma(p^d_t, 1) - p^d_t, \\ \omega^d_{n,t+1} \sim \Gamma(n^d_t, 1) - n^d_t, \end{array}\right\} \Gamma(x, y) -$$ gamma distribution with shape parameter x and scale parameter y

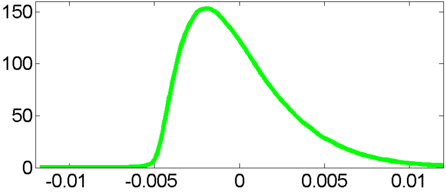
Bad Environment-Good Environment probability density function



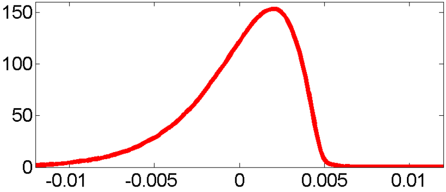
Time-varying variances: Probability density functions

- p_t can be interpreted as good variance and n_t as bad variance

Large p_t- Good environment: positive unscaled skewness



Large n_t- Bad environment: negative unscaled skewness



Advantages of BEGE Distribution

- Fit non-Gaussian features of macroeconomic (Bekaert and Engstrom, JPE 2016) and financial data (Bekaert, Engstrom, and Ermolov, JoE 2015) well
- Theoretically tractable: unscaled moments linear functions of p_t and n_t

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General Overview

- US quarterly observations 1959Q2-2015Q2
- Identify macro expectations and shocks using VARMA(1,1) on real activity and inflation data
- Filter demand and supply shocks from macro shocks using classical minimum distance (CMD)
- Estimate BEGE dynamics of demand and supply shocks using approximate MLE (Bates, 2006)

Identify Macro Expectations and Shocks

- VARMA(1,1) on 6 variables (based on AIC):
  - Real GDP growth
  - Core and aggregate inflation
  - Unemployment gap
  - 1 quarter and 10 year Treasury yields
- Extract:
  - Expectations of real GDP growth, inflation, core inflation + unemployment gap
  - Shocks to real GDP growth, inflation, core inflation and unemployment gap

Filter Demand and Supply Shocks

- Shock structure:

$$\begin{bmatrix} \epsilon_t^g \\ \epsilon_t^\pi \\ \epsilon_t^{\text{core}} \\ \epsilon_t^{\text{unemp}} \end{bmatrix} = \underbrace{\Sigma}_{4\times 2} \begin{bmatrix} u_t^d \\ u_t^s \end{bmatrix} + \underbrace{\Omega}_{4\times 4} \begin{bmatrix} \xi_t^g \\ \xi_t^\pi \\ \xi_t^{\text{core}} \\ \xi_t^{\text{unemp}} \end{bmatrix}$$

- Ω - diagonal with ξ_t^g, ξ_t^π, ξ_t^{core}, ξ_t^{unemp} $\sim$ i.i.d. distribution with 1 variance and 0 skewness and excess kurtosis
- Percentage of variance attributed to ξ_t^g, ξ_t^π, ξ_t^{core}, ξ_t^{unemp} is the same across all 4 macro series
- Estimate Σ and Ω via CMD: matching 36 unconditional second, third, and fourth order moments of macro shocks
- Filter u_t^d and u_t^s with a Kalman filter

Non-Gaussian Aspects of Macro Data

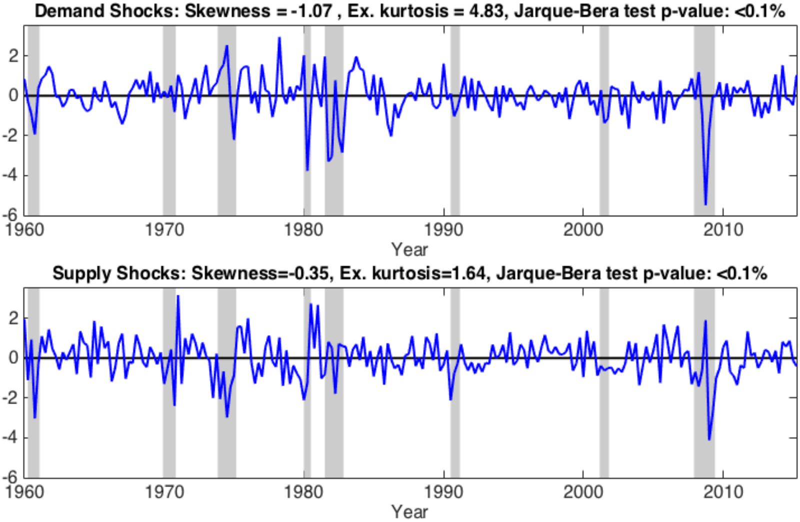
- 12 out of 26 third and fourth order macro shock moments are individually statistically significant at least at the 10% level
- 26 third and fourth order macro shock moments are jointly significant at the 1% level

▸ Moment Values

	Demand	Supply
GDP growth	0.43	0.32
	(0.16)	(0.11)
Inflation	0.26	-0.27
	(0.06)	(0.07)
Core inflation	0.19	-0.17
	(0.05)	(0.04)
Unemployment gap	-0.16	-0.11
	(0.05)	(0.02)

Other shocks account for 45% of macro shocks variance

Demand and Supply Shocks

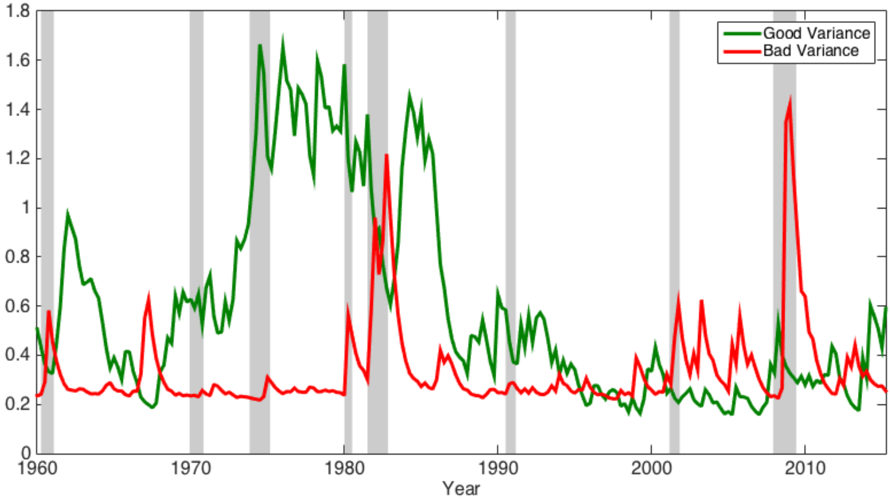


Estimate BEGE Dynamics

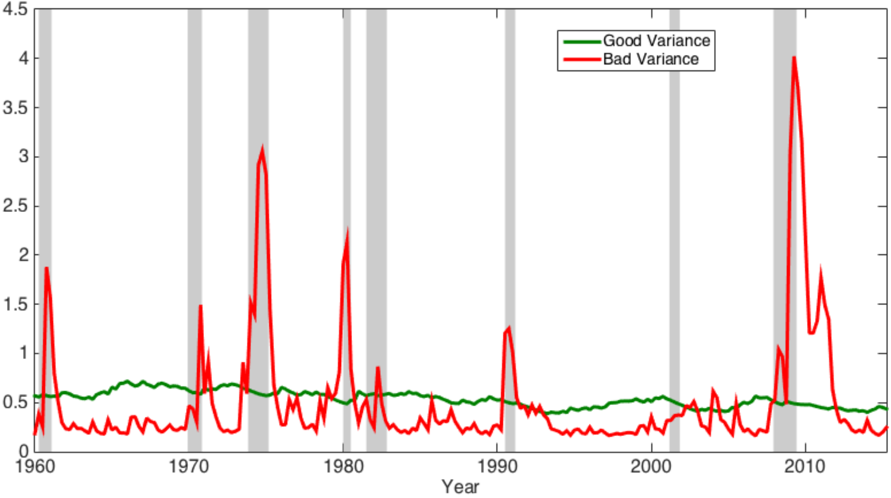
- BEGE variances p_t^d, n_t^d, p_t^s, and n_t^s follow autoregressive square-root-type processes
- Bates (2006) approximate maximum likelihood method to estimate parameters and filter conditional variances

Macro risk processes

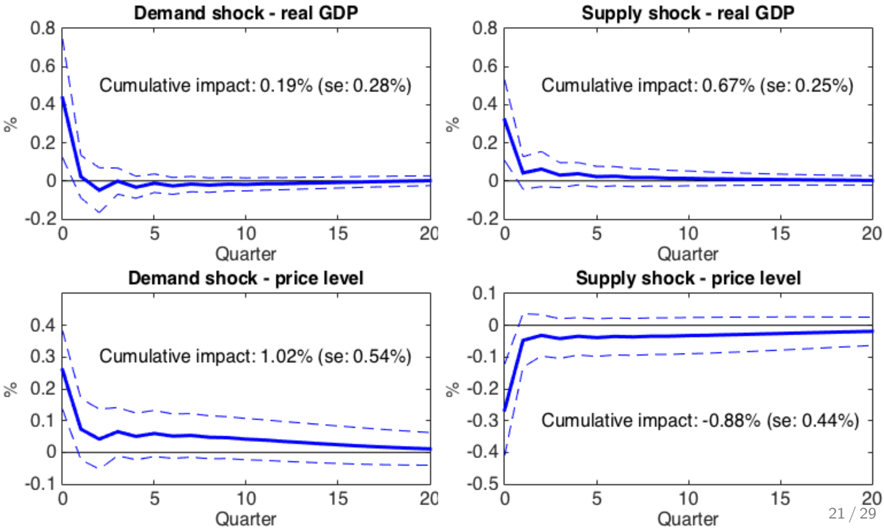
Demand Variance Decomposition



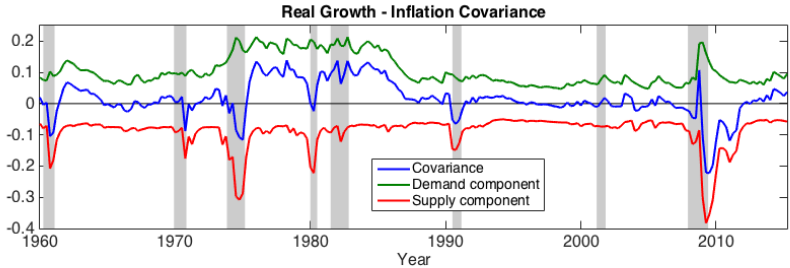
Supply Variance Decomposition

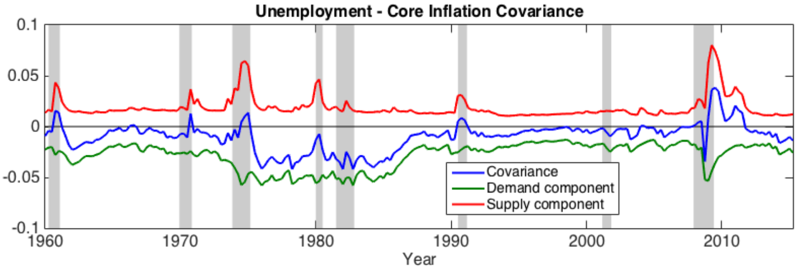


Impulse Responses



Time-varying Real-Nominal Covariance



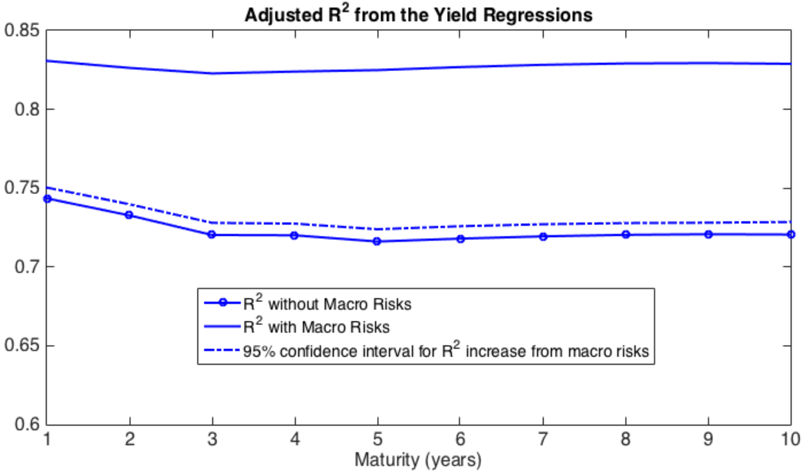


State Variables

- Macro level factors (Ludvigson and Ng, 2009, - type):
  - Expected real GDP growth
  - Expected inflation
  - Expected core inflation
  - Unemployment gap
- Second/higher order moments=**macro risks**:
  - p_t^d - good (positive skew) demand variance
  - n_t^d - bad (negative skew) demand variance
  - p_t^s - good (positive skew) supply variance
  - n_t^s - good (negative skew) supply variance

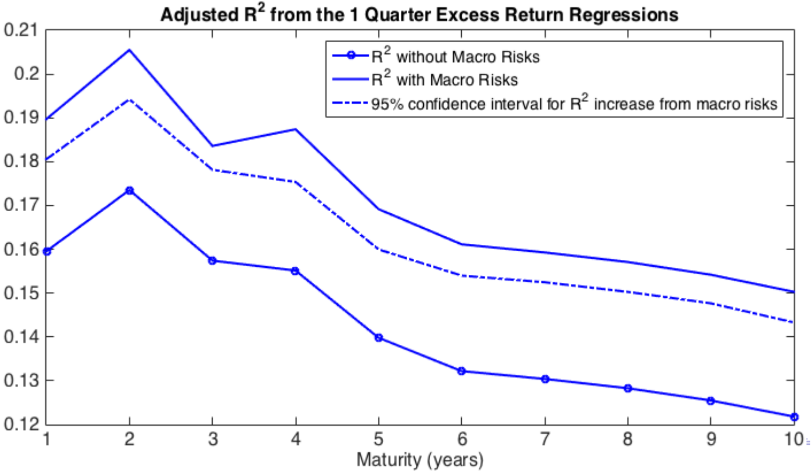
Explanatory Power for Yield Levels

- Predictors: 4 macro level factors +macro risks
- Confidence interval is Bauer and Hamilton (2015) bootstrap confidence interval



Explanatory Power for Excess Returns

- Predictors: 4 macro level factors +macro risks
- Confidence interval is Bauer and Hamilton (2015) bootstrap confidence interval

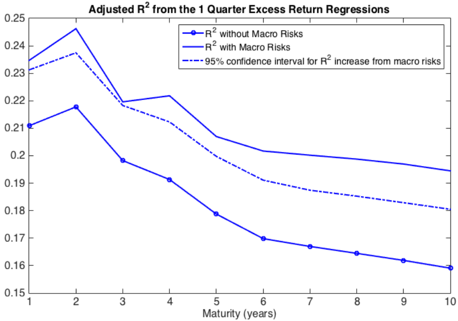


1 Quarter Excess Return Regressions

	1 year bond	5 year bond	10 year bond
macro level factors	...	...	...
p_t^d	0.0006 (0.0020)	0.0063 (0.0096)	0.0211 (0.0208)
n_t^d	-9.8329 (2.7119)	-44.0961 (10.5535)	-69.0965 (24.7824)
p_t^s	0.0062 (0.0016)	0.0208 (0.0100)	0.0168 (0.0154)
n_t^s	0.0457 (0.0926)	0.2028 (0.3440)	0.4436 (0.5772)

Explanatory Power for Excess Returns Over Yield Factors

- Predictors: 4 macro level factors + 3 yield curve factors +macro risks
- Confidence interval is Bauer and Hamilton (2015) bootstrap confidence interval



- Similar results for Ang-Piazzesi (2003) factors here

Term Premium

- Blue Chip forecasts based 10 year term-premium: semi-annually 1986Q2-2015Q2

macro level factors	p_t^d	n_t^d	p_t^s	n_t^s
...	6.84E-06	-1.4758	0.0480	0.1046
...	(2.65E-04)	(0.3672)	(0.0949)	(0.0925)

- Adjusted R^2 without macro level factors only: 0.6437 (95% confidence upper bound 0.6814)

- Adjusted R^2 with macro risks: 0.7072

Conclusions

- Novel method for extracting aggregate demand and supply shocks based on exploiting non-Gaussian features of data
- Characterizing macroeconomic dynamics via AD/AS shocks
- Demand-supply composition of macroeconomic shocks matters for bond and term premia
- Term-structure model with AD/AS macro risks (work in progress):
    - Economic intuition
    - Non-Gaussian features
    - Closed form solutions!

Appendix: BEGE Moments

- $u_t \sim \sigma_p(\Gamma(p_t, 1) - p_t) - \sigma_n(\Gamma(n_t, 1) - n_t)$
- Variance: $\sigma_p^2 p_t + \sigma_n^2 n_t$
- Unscaled skewness: $2\sigma_p^3 p_t - 2\sigma_n^3 n_t$
- Unscaled excess kurtosis: $6\sigma_p^4 p_t + 6\sigma_n^4 n_t$

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Appendix: Macro Risk Processes

- Macro risks are persistent and driven by the realization shocks capturing volatility clustering (Gourieroux and Jasiak, 2006):

  $$p^d_{t+1} = \bar{p}^d + \rho^d_p(p^d_t - \bar{p}^d) + \sigma^d_{pp}\omega^d_{p,t+1}$$

- Similar processes for n^d_t, p^s_t, and n^s_t

- If $\sigma_{pp} < \rho_p$, macro risks never hit a zero-lower bound

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Appendix: Unconditional Moment Values 1/3

Scaled skewness:

	inflation	real growth	core inflation	unemployment gap
data	-1.2632	0.1275	0.1866	0.6860
standard error	(0.9124)	(0.3064)	(0.4598)	(0.2372)
fitted	-0.2328	-0.3188	-0.2804	0.3576

Excess kurtosis:

	inflation	real growth	core inflation	unemployment gap
data	10.3646	1.6505	2.3854	1.9179
standard error	(5.1438)	(0.7314)	(1.1802)	(0.6808)
fitted	0.4552	0.8090	0.6070	0.9314

Appendix: Unconditional Moment Values 2/3

Coskewness:

	$infl^2 \times rgrw$	$infl^2 \times cinfl$	$infl^2 \times ugap$	$rgrw^2 \times infl$
data	-0.7728	-0.2339	0.7322	-0.2404
standard error	(0.4328)	(0.3097)	(0.4016)	(0.1780)
fitted	-0.2316	-0.2474	0.2416	-0.2982
	$rgrw^2 \times cinfl$	$rgrw^2 \times ugap$	$cinfl^2 \times infl$	$cinfl^2 \times rgrw$
data	-0.1860	0.1877	0.0814	-0.1920
standard error	(0.1912)	(0.3358)	(0.3184)	(0.1459)
fitted	-0.3185	0.3314	-0.2632	-0.2721
	$cinfl^2 \times ugap$	$ugap^2 \times infl$	$ugap^2 \times rgrw$	$ugap^2 \times cinfl$
data	0.0847	-0.1989	-0.4535	-0.0265
standard error	(0.2143)	(0.1384)	(0.3097)	(0.2290)
fitted	0.2833	-0.3172	-0.3443	-0.3392

Appendix: Unconditional Moment Values 3/3

Co-excess Kurtosis:

	$infl^2 - rgrw^2$	$infl^2 - cinfl^2$	$infl^2 - ugap^2$
data	1.7346	0.6331	1.2858
standard error	(1.0385)	(0.3624)	(0.7526)
fitted	0.6069	0.5257	0.6511
	$rgrw^2 - cinfl^2$	$rgrw^2 - ugap^2$	$cinfl^2 - ugap^2$
data	0.7458	1.1438	0.7440
standard error	(0.3166)	(0.5808)	(0.2958)
fitted	0.7088	0.8680	0.7519

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Appendix: Yield Regression Coefficients

	1 quarter	1 year	5 years	10 years
Constant	1.2182	1.2616	1.4215	1.5314
	(0.0665)	(0.0712)	(0.0733)	(0.0683)
$E_t c_{t+1}$	1.1418	1.1072	0.9680	0.8605
	(0.0827)	(0.0928)	(0.1006)	(0.0920)
$E_t \pi_{t+1}$	-1.2914	-1.5094	-1.7303	-1.6230
	(0.2286)	(0.2420)	(0.2986)	(0.2995)
$E_t g_{t+1}$	0.4965	0.5663	0.6054	0.5486
	(0.1144)	(0.1264)	(0.1455)	(0.1279)
u_t	-0.0684	-0.0638	0.0042	0.0424
	(0.0350)	(0.0357)	(0.0329)	(0.0254)
p_t^d	-8.10E-05	-3.39E-05	5.00E-05	4.25E-05
	(9.53E-05)	(9.31E-05)	(8.60E-05)	(9.35E-05)
n_t^d	0.4714	0.4212	0.3177	0.2864
	(0.3179)	(0.3390)	(0.3111)	(0.2793)
p_t^s	0.0232	0.0240	0.0180	0.0121
	(0.0076)	(0.0072)	(0.0055)	(0.0047)
n_t^s	-0.1802	-0.1915	-0.1862	-0.1665
	(0.0405)	(0.0479)	(0.0514)	(0.0483)

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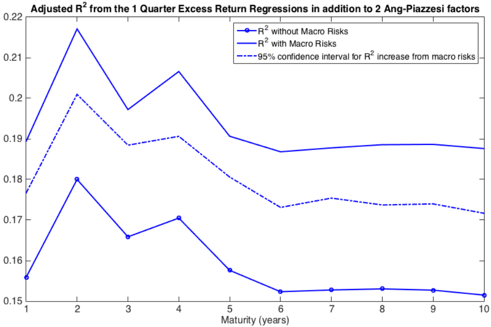
Appendix: Explanatory Power for Excess Returns over Ang-Piazzesi Factors

- Predictors: 4 macro level factors +Ang-Piazzesi (2003) factors + macro risks
- Confidence interval is Bauer and Hamilton (2015) bootstrap confidence interval



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